Remarks

Reconsideration and allowance of the subject patent application are respectfully requested.

Claims 1-38 and 40-59 were rejected under 35 U.S.C. Section 101 as allegedly being directed to non-statutory subject matter. Claims 1-38 and 40-59 were rejected under 35 U.S.C. Section 101 as allegedly not being supported by either a specific or substantial utility or a well-established utility. Claims 1-38 and 40-59 were further rejected under 35 U.S.C. Section 112, first paragraph, because one skilled in the art allegedly "would not know how to use the claimed invention." While not acquiescing in these rejections, independent claims 1, 9, 17, 25, 33, 35, 36, 52 and 57 have been amended to describe that the output signals are for "an effector or a user interface." Example support for this feature can be found in Figure 3 and page 23, (numbered) line 5 et seq. Applicant respectfully submits that this provides an "identified practical application" for the claimed systems and methods and withdrawal of the various rejections based on the alleged lack of utility is respectfully requested.

Claims 1-38 and 40-59 were rejected under 35 U.S.C. Section 102(b) as allegedly being "anticipated" by Austin, "Rapid Learning with a Hybrid Neural Network" (referred to in the office action as "Austin_045.pdf"). For the reasons set forth below, Applicant respectfully traverses this rejection.

Austin_045.pdf discusses a hybrid neural-network (HNN), combining flexibility with generalization, using a multi-layered, back-propagation network (MLN), and with learning-speed using an N-tuple pattern recognition network (NTR).

MLN is essentially a least-square error-learning algorithm, adjusting weights of a feed-forward network to minimize nonlinear outputs with training examples. NTR n-tuple learning begins with a threshold driven summing unit of binary segmentation of the patterns into a coding based on 3 groups (tuples; 3 2-bit pairs). Learning uses binary weights, and hence is very fast. The total patterns are a combinatorial function of N, qth sized-tuples taken j values of the threshold setting ranging from T to q. Thus for a small number of threshold values, the generalized set will be small, but not maybe as accurate, unless N is large. The success of the

NTR approach is to partially orthogonalize the input patterns through the use of the decoders, before learning begins. Hence, the HNN hybrid network uses the decoder frontend of the NTR, feeding the backend of the MLN approach.

The specific discussions of Austin_045.pdf cited in the office action deal with the section 2.0 "N tuple networks", sub-section "Coupling the MLN and N tuple networks" beginning on page 4 of the paper, and continuing onto page 5 with an n-tuple frontend example (with Fig 1a) (note that there is no Fig 1b), and then onto Fig. 2 on page 6, showing the various networks studied in the reported investigations {e.g., Fig 2a) HNN-A; Fig 2b) HNN-B; Fig 2c) HNN-C with all varying with the use of the number of hidden layers and their interconnection; Fig 2d) MLN with two, fully interconnected layers; Fig 2e) SLN with one, fully interconnected layer; and Fig 2f) an N-tuple without interconnection other than in the decoding, similar to the backend part of the Fig 1a) network}.

In summary, Austin_045.pdf describes the use of threshold-driven, binary-encoded tuple inputs, which is not summed and thresholded, having the output being combined as a frontend input encoder, providing a slight input correlation from a partial orthogonalization on the input patterns, feeding forward to various two layer back-propagation learning networks, having variations in the second layer interconnections (Fig 2a and Fig 2b), with an omission of the second layer (Fig 2c), without the encoding as a back-propagation learning network with two (Fig 2d) and one (Fig 2e) fully interconnected layers, and finally as just a single, summed encoder {Fig 2f), similar to Fig 1a)}, but without the back propagation backend. Thus, the results showed that the limited pattern examples tested, with only 20 feature inputs, favored the combined NTR encoder with the MLN (Fig 2a).

Beyond containing the terms "input", "output" and "partially orthogonalise", Applicant respectfully submits that there is no relationship between Austin_045.pdf and the pending claims.

By way of example, Applicant finds no mention in Austin_045.pdf of the partially orthogonal N-dimensional object space specified in each of the independent claims. Indeed, Austin_045.pdf makes no mention of N- (or M-) dimensional spaces. Instead, Austin_045.pdf relates to "<u>n-tuple networks</u>" used in a hybrid network, wherein <u>the patterns presented to the network</u> are "partially orthogonalized". See Austin_045.pdf, page 4 ("If the input to a MLN is

first partially othogonalized by a set of decoders, then the problem of classification is made easier for the MLN."); see also Austin_045.pdf, page 5 ("These [decoders] are used, as indicated above, it [sic] partially orthogonalise the patterns presented to the network."). The n-tuple networks of the hybrid network are not N-dimensional object spaces and the partial orthogonalizing of inputs to the network in no way relates or corresponds to partially orthogonalising such N-dimensional spaces.

For these reasons alone, Austin_045.pdf cannot anticipate the pending claims.

Moreover, the Austin neural network input data patterns (up to 20 components in Austin_045.pdf) are not user inputs responsive to training stimulation as specified in the independent claims. Austin_045.pdf describes the input as being made up of six binary elements, broken up into 3 groups (or tuples), each of 2 elements. See Austin_045.pdf, page 2. There is nothing that describes these inputs as being responsive to or indicative of training stimulation. For this additional and independent reason, Austin_045.pdf cannot anticipate the pending claims.

Further, with respect to claims 35, 36, 52 and 57, there is no disclosure in Austin_045.pdf of mapping an N-dimensional space to one or more M-dimensional sub-spaces. The disclosure of Austin_045.pdf referenced in connection with this feature is the "coupling the MLN amd N tuple networks". However, this disclosure relates to uniting "two different networks with very useful properties into one network that can be tuned to provide a mix of the required properties." Austin_045.pdf, page 1. This has nothing to do with any "conversion" as suggested in the office action and does not at all relate to mapping an N-dimensional space to one or more M-dimensional spaces as claimed. For this additional and independent reason, claims 35, 26, 52 and 57 and their dependent claims cannot be anticipated by Austin_045.pdf.

Numerous features set forth in the dependent claims are likewise not disclosed by Austin_045.pdf. By way of example, there is no disclosure of the worldliness specified in claims 3, 11, 19, 27, 37 and 46. Similarly, there is no disclosure of the subspace projection operators of claims 41-45.

The pending claims are believed to be allowable and favorable office action is respectfully requested.

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Serial No. 09/658,275
Response to Office Action dated February 14, 2006

Should any issues remain, the Examiner is invited to telephone the undersigned at the number listed below.

Respectfully submitted,

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